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Opinion Mining for Amhara Broadcasting Agency News

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FACULTY OF COMPUTING

Opinion Mining for Amhara Broadcasting Agency News

MSc Thesis

By

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DECLARATION

I, the undersigned, declare that the thesis comprises my own work. In compliance with internationally accepted practices, I have acknowledged and refereed all materials used in this work. I understand that non-adherence to the principles of academic honesty and integrity, misrepresentation/ fabrication of any idea/data/fact/source will constitute sufficient ground for disciplinary action by the University and can also evoke penal action from the sources which have not been properly cited or acknowledged.

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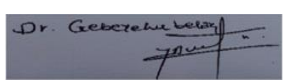
Advisor's Signature: 

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I hereby confirm that the changes required by the examiners have been carried out and incorporated in the final thesis.

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As members of the board of examiners, we examined this thesis entitled "Opinion Mining for Amhara Broadcasting Agency News" by *Maru Kindeneh Jemebr*. We hereby certify that the thesis is accepted for fulfilling the requirements for the award of the degree of Masters of science in "Information Technology".

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Abstract

Sentimental analysis or Opinion mining is used in analyzing the important opinion from the reviews generated by the users. The main objective of Sentiment analysis is classification of opinions/sentiments. It classifies the given text in three levels: document level, sentence level, and entity/aspect level. The accumulation of vast and unstructured opinions on many domains has been making information gaining difficult. Opinion mining is the opening technique towards tackling this problem. In this research work, an Opinion Mining model is built for classifying Amharic opinionated text into positive, neutral and negative. The experiments are conducted using 787 Amharic opinionated texts collected from Amhara broadcasting agency Facebook page and YouTube cannel users' sport and business news comments. We use term frequency invers document frequency feature extraction method and implement supervised classifiers from the Natural Language Toolkit in Support Vector Machine algorithm. The design and development of this thesis work is based on the machine learning approach. The experiment results 83.24% Accuracy in Support Vector Machine algorithm, Generally, the results are encouraging despite the morphological challenge in Amharic, the data cleanness and small size of data. Negations and valence shifters will be considered as a feature in ML approach because their presence in the sentence can result in changing the sentiment of the whole comment like "ጥሩ - nice" implying positive sentiment if preceded by "ጥሩ አይደለም– not good" would then imply negative sentiment.

Keywords: Opinion, Opinion Mining, Opinion Holder, SVM Algorithm, Sentence Level, Classification, Extraction, Machine Learning

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ABBREVIATION

APIs	application program interfaces
CTRW	Choose the Right Word
GI	General Inquirer
IEEE	institute of electrical and electronics engineering
JSON	java script
LDA	latent Dirichlet allocation
Maxent	maximum entropy
MNB	Multinomial NB
NB	Naive Bayes
NLP	natural language processing
NMF	Non-negative matrix factorization
OP	opinion mining
SA	sentiment analysis
SGD Classifier	Stochastic Gradient Descent
SSNMF	Semi-supervised version of NMF
SVM	support vector machine
TF	Term Frequency
TF-IDF	Term Frequency Inverse Document Frequency
TM	Text Mining
WSD	word sense disambiguation

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CHAPTER ONE

INTRODUCTION

Sentimental analysis or Opinion mining is used in analyzing the important opinion from the reviews generated by the users. When any decisions are to be made regarding the delivered services, the purchase of new product, software or electronic products the people are very much attracted in obtaining the reviews from the various websites, blogs or discussion forums. In such case opinion mining or sentimental analysis is used broadly which deals with tracking the attitude of the people regarding a particular product or topic (Vidhya, 2016).

Customers of online services, in many cases, do not have well-defined expectations about the service. Therefore, understanding the sentiment of the customers after the service delivery can be of great help for evaluating their satisfaction regarding the services we provide. Internet permits several changes in economic, social, political, cultural and philosophical relations. These changes are still open, and continue to happen as the Internet itself redefines its scope and reach. To keep up in a competitive market, it’s important for the companies to worry about the quality of the provided services rather than provide money services. The quality in services is a comparison between the client’s expectations and the service’s performance (Sassi, 2014).

Social media is one of the main forums to express opinions in different domain. Sentiment analysis is the process in which information is extracted from the opinions, appraisals and emotions of people in regards to entities, events and their attributes (Liu, Sentiment Analysis and Subjectivity, 2010). Opinion Mining is to analyze and classify the user generated data like comments, reviews, blogs, comments, articles. (Poobana, 2015). In order to enhance customer satisfaction and their following skills, it has become a common practice for online deliverer to enable their customers to review or to express opinions on the program that they watch. A common user becoming comfortable with the Internet, an increasing number of people are writing reviews. Many popular products can get hundreds of reviews at some large trading sites. This makes it very hard for a potential customer to read them to help to make a decision on whether to buy the product.

Sentiment analysis or Opinion mining use some algorithm techniques to categorize the user opinions into positive, neutral and negative classes. This categorization of text is called polarity of text. Although sentiment analysis can be applied to any human language, some of the approaches could be language specific. The majority of sentiment analysis studies that have been conducted are for English language and the methods cannot be directly implemented on other languages. Languages in the Semitic family that are typically rich in regard to morphology are not exceptions in this regard. The root-template morphology that characterizes Semitic languages results in high degree of word productivity and hence data sparseness which demanded natural language processing (NLP) preprocessing techniques to analyze sentiments.

Amharic is one of the sub-Saharan countries Ethiopian's working language which is written left-to-right in its own unique script which lacks capitalization and in total has 275 characters mainly consonant-vowel pairs. It is the second largest Semitic language in the world after Arabic and spoken by about 40% of the population as a first or second language but current population estimated to 102 million (Wang, 2018).

The main objective of Sentiment analysis is classification of opinion/sentiment. It classifies the given text in three levels: document level, sentence level, and entity/aspect level.

In document level classification, a single review about a single topic is considered that is positive, neutral or negative opinion. We cannot conclude best product by giving one opinionated word. There for subjectivity/objectivity classification is very important in this type of classification. The irrelevant sentences must be removed from the processing activity. Here both methods supervised and unsupervised learning methods can be used for the document level classification. In sentence level classification positive and negative opinion is taken by this can identify a program strategy. The supervised learning methods are used for the text classification. In aspect-level classification "not bad" opinion is taken to prove a good product. Opinion mining is a Natural Language Processing and Information

Extraction task that aims to obtain writer's feelings expressed in positive or neutral or negative comments, questions and requests, by analyzing a large number of documents. Translating a piece of text to a feature vector is the basic step in any data driven approach to Sentiment analysis. Term frequency has always been considered essential in traditional Information Retrieval and Text Classification tasks (Jayashri Khairnar, 2013).

Support vector machine, Maximum Entropy (MaxEnt) and naïve bayes classifiers are the most commonly used algorithm in opinion mining. SVM are large-margin, rather than probabilistic, classifiers, in contrast to Naive Bayes and MaxEnt. There are some questions in opinion mining, among them the foremost questions are classification accuracy so classification accuracy can be increased by selecting good preprocessing, feature selection and classification techniques (Jadav, 2016).

Two types of techniques have been applied in opinion mining applications: machine learning and semantic orientation. The machine learning approach applied to this problem typically belongs to supervised classification in general and text classification techniques in particular for opinion mining. This kind of technique tends to be more accurate because each of the classifiers is trained on a collection of representative data known as corpus. Thus, it is called "supervised learning". In contrast, using semantic orientation approach to opinion mining is "unsupervised learning" because it does not require prior training in order to analysis the data. Instead, it measures how far a word is inclined towards positive and negative (Zhou, Movie Review Mining: a Comparison between Supervised and Unsupervised Classification Approaches, 2005).

1.1. Statement of the Problem

Due to the rapid growth of opinionated comments, reviews and posts on the Web, the need for finding relevant sources, extract related sentences with opinions, summarize them and organize them to suitable form is becoming very high. Opinion mining can play an important role in satisfying these needs. Amhara broadcasting agency is one of the Amhara organization that deliver relevant information for the population among the organization's service sport and business news are common. Currently the agency receive comment from their customer for their services are through phone call, direct contact and from the site by reading that much comments which is difficult to address all customer opinions. That is spadework to analysis the customer opinion to enhance the performance of the Amhara broadcasting program to satisfy their followers, so we want to develop a model that mining the opinions of the large population by using machine learning SVM algorithm.

The research issue summarized as:

- How to preprocess the data effectively using appropriate technique for sentiment analysis of Amharic text?
- How to perform feature extraction and categorization for sentiment analysis to identify the news context?
- How to model human cognitive towards opinion mining for the best of information from news?
- What classification model works for classifying Amharic opinion mining?

1.2. Objective of the Study

1.2.1. General Objective

The general objective of this study is to develop a model to opinion mining for Amhara mass media agency sport and business news users' comments.

1.2.2. Specific Objectives

To address the research issues, the following specific objectives are formulated.

- To preprocess the collected comments text data effectively for Amhara broadcasting agency sport and business news comments opinion mining.
- To reduce the problem of opinion mining of Amharic text sentiment classification by using the selected algorithms.
- To construct a predicative model for analyzing Amhara broadcasting agency business and sport news comment.

- Create a prototype that presents the outputs of the analysis and summarizes the opinions both through the computer and on handheld devices.

1.3. Methodology

To achieve the general and specific objectives listed above we will conduct the following method.

1.3.1. Data Source

The data source for this study was collected from internet, which is the datasets used for conducting the experiment were collect from Amhara broadcasting agency Facebook page and YouTube channel comments of the customer.

1.3.2. Data Collection

The data were collected online from Amhara broadcasting agency Facebook page and YouTube channel of customers comments. For this study two types of dataset are preparing for training data and testing data to conduct the prototype of opinion mining for Amhara broadcasting agency sport and business news in Amharic text. For the training dataset, a document which contains a set of representative text from Amhara Mass Media sport and business news comments are taken to train our opinion mining algorithm. The data that are collected from the data source are classified in to three positive, negative, neutral. For the purpose of this study, we will collect totally 787 customer comments. From the dataset 70% training 30% teste data will be taken.

1.3.3. Design Procedures /Data Preprocessing

The proposed method consists of the following steps: we collect customers' comments from the social media (Amhara broadcasting agency Facebook page and YouTube channel comment), collected reviews were preprocessed and opinion were analyzed then the analyzed text comments were extracted and then the extracted opinionated text comment were labeled in to its polarity. The stop words and stemming words are removed at the stage of preprocessing. The extracted texts were analyzed by reviewer and classify the text into positive, negative and neutral then the product is ranked.

1.3.4. Tools and Techniques

The main tools that are used in conducting this research work are:

Python is a popular programming language. It was created in 1991 by Guido van Rossum. For extract data from internet and implementing the algorithms we use Facebook, Instagram or tweeter online comment extractor https://exportcomments.com/ which extracts Facebook post comment in to excel file, and YouTube comment scraper http://ytcomments.klostermann.ca/ for extracting YouTube comments.

1.4. Scope and Limitation of the Study

Sentiment analysis is a complex and recent research discipline that requires the effective analysis and processing of documents. Since there are no publicly available Natural Language Processing (NLP) tools and other resources for Amharic language that can be integrated with our model, the scope of our research work is:

- Limited to sentiment (polarity) mining (only positive, negative or neutral) classification.
- The opinion holder identification and reasons for positive and negative classifications are not covered in this research work.

Attention is given to most common Amharic words used to express opinions "**ጥሩ፣ ደስ ይላል፣ በ ጣም ጥሩ፣ መልካ ም ፣ቆንጆ ነው ፣ያምራል ወዘተ**" for positive opinions and "**መጥፎ ፣ አይመችም ፣ ደስ አይልም: አያምርም፣ግም ነው፣ያስጠላል ወዘተ**" for negative opinions. Because of their complicated nature, Amharic expressions such as **"ቅ ኔ ያዊ አ ነ ጋ ገ ር"** are out of the scope of this research work። and Word **ሲጠብቅ እና ሲላላ የትርጉም ልዩነት የሚያምጠዉን አያካትትም፤ ለምሳሌ ገና** when **ና ጠብቆ ሲነበብ** (Criss mass) **ገና** when **ና ላልቶ ሲነበብ** (late).

1.5. Significance of the Study

This study conducted on Amhara broadcasting agency on sport and business news customers comments opinion mining which has targeted for optimizing the broadcasting performance. The collected tata uses for other researchers to perform similar research work. The media organizations need such researches in order to identify what the customer want, so that the media organizations could produce contents that better suit their customer.

In addition to that, the study may tell the strengths and weaknesses of the broadcast leading to an improved quality in the program contents and presentations. It is also believed that the study has the significance of sparking insights for other similar researches in the area of customer research endeavors specifically on programs that are of concern to the target customer.

1.6. Organization of the Thesis

The study comprises five chapters. In the first chapter are the background of the study, the general and specific objectives, the research questions, the significance, the scope and limitations of the study. Also, briefly - by way of providing a backdrop of the focus of the study it introduces the history of the opinion mining for Amhara broadcasting agency and its programmers'.

Review of related literature presented in chapter two, provides the basic literature on various theories with the aim of laying down the theoretical basis underpinning this study and providing understanding as to how customers were perceived in various media theories.

Chapter three discusses and in a way justifies the methodology used for the study.

Chapter four presents the data and analysis of the findings under four general themes.

The last chapter, chapter five concludes by summarizing the findings and giving recommendations.

CHAPTER TWO

LITERATURE REVIEW

2.1. Introduction

The two main types of textual information available in any texts are: facts and opinions. Facts are objective statements about entities and events in the world but opinions are subjective statements that reflect people's sentiments or perceptions about the entities and events.

Automatic sentiment analysis in texts, also called opinion mining, has attracted considerable attention in recent years, primarily because of its potential use in marketing study. It aims to answer questions such as 'is the customer who sent a mail to an after-sale service particularly dissatisfied?',' are the opinions about product posted in blogs positive or negative?', what is the image of political party or leader in the press?'. All these questions, which are related to the way something is presented or evaluated in a text, are particularly difficult for traditional information extraction techniques, which are interested with factual information. The sudden eruption of activity in the area of opinion mining and sentiment analysis, which deals with the computational treatment of opinion, sentiment and subjectivity in the text, has occurred at least in a part as a direct response to the surge of interest in new systems that deal directly with opinions as a first-class object (Selama , 2010).

In this section, a review of existing literature on sentiment analysis is done. A description is made employment of machine learning and statistical techniques to determine sentiments in Amhara broadcasting agency sport and business news opinions. A review of the application of various techniques for sentiment analysis is also done.

2.2.The Amharic Language

Abriham Getachew deeply discuss about Amharic Language (Abreham , 2014), Amharic (አማርኛ) is widely spoken language and is one of the Semitic languages which have its own script. It is the second most-spoken Semitic language in the world, after Arabic, and the authorized working language of the Federal Democratic Republic of Ethiopia. The language uses its alphabet, ፊደል (fidal), inherited from the Geez (Ethiopic) language. Geez is an ancient South Semitic language which now serves only as the liturgical language of the Ethiopian Orthodox Tewahedo Church. Fidäl is a syllabary writing system where the consonants and vowels co-exist within each graphic symbol. Unlike majority of its Semitic scripts, such as Arabic and Hebrew, fidal is written from left to right. The Amharic writing system contains 33 consonants, each having seven ‘orders’ or shapes depending on the vowel with which a given consonant is combined.

Abriham classifies Amharic grammar writing words in to eight depending on Mersehazen work. These are preposition, noun, conjunction, interjection, verb, adjective, pronoun, and adverb. Amharic manuscripts are known from the 14th century and the language has been used as a general medium for literature, journalism, education, and so on. A wide variety of Amharic literatures including books, religious writings, fiction, poetry, plays, and magazines are available both in printed and machine-readable format. they discuss detailly about the Amharic writing system, the Amharic characters (filed), nature of Amharic character, character redundancy, Variations due to Pronunciations, Amharic Compound Words practice, Other cases of word variation and Amharic Punctuation marks on their paper.

2.2.1 Problem of Amharic writing system

There are a number of problems associated with Amharic writing system which are challenging natural language processing of Amharic documents; which are dealt below. Redundancy of some characters: sometimes more than one character is used for similar sound in Amharic (Sintayehu, 2001). Though the various forms have their own meaning in

Ge'ez, there is no clear-cut rule that shows its purpose and use in Amharic according to (Bender, 1976).

Character	Other form/s of the character
ሀ (hä)	ሐ and ኀ
ሠ (sä)	ሰ
አ (ä)	ዐ
ጸ (tsä)	ፀ

Table 2: 1 Illustrates the Different Forms of Amharic Characters with Similar Sound.

The problem of the same sound with various characters is not only observed with core characters, but also exhibited in the same order of characters. For example, ሀ and ሃ, ኀ and ኃ; አ and ኣ; etc (Hailemeskel, 2003). The use of various forms of characters for the same sound poses a problem in the process of feature preparation for the classifier learning since the same word is represented in different forms. For example, the word 'ጸሀይ' ('sun') can be represented in Amharic as ጸሀይ, ጸሐይ, ጸኀይ, ፀሀይ, ፀሐይ, ፀኀይ, etc. Amharic characters with different forms of the same sound Character other form/s of the character.

2.2.2. Redundancy of some characters

Sometimes more than one letter is used to represent similar sound in Amharic language. For instance, letters "ሀ" and "ኀ"; "ጸ" and "ፀ"; "ሰ" and "ሠ" have similar sounds. In the old literature of Amharic texts, the use of various forms of characters for the same sound has a problem in the process of feature preparation for the classifier learning. However, current literatures do not have such problems since it has only one letter for one sound. As a result, the alphabet "ኀ", "ጸ" and "ሠ" are no more in use in writing Amharic document.

2.2.3 Spelling variation of the same word

One can imagine how the meaning of the original word is diverted to different contexts. Spelling variation of the same word: the same word is written in various forms (Hailemeskel, 2003). For example, the word 'ሰምቶአል' ('he hears') can be written in Amharic as ሰምቶአል, ሰምቷል, ሰምትዋል, etc. Spelling variation may happen also in the case of translating foreign word to Amharic. For instance, the word 'ቴሌቪዥን' ('television') can be written as ቴሌቭዢን, ቴሌቭዥን, ቴሌቪዥን, etc.

2.3. Opinion Mining/Sentiment Analyses

Chinsha, Shibily Joseph studies are focus on the aspect-based opinion mining of restaurant reviews, i.e. given a set of comments of Amhara broadcasting agency business and sport news we get a sentiment profile of its important features automatically. Proposed method uses SentiWordNet for assigning priority values to opinion words, which is a dictionary of opinion words. (Joseph, 2014).

Freimut Bodendorf, Carolin Kaiser are presented that opinion mining approach belongs to the category of feature-based opinion mining and aims at extracting and analyzing customer opinions on products in forum postings. It comprises four succeeding steps: selection, extraction, aggregation, and analysis. The goal of the authors is to detect strengths and weaknesses of different (e.g., rival) products and to re-veal associations between product features. (Kaiser, 2010)

Original Naïve Bayesian algorithm using Supervised Term Counting based approach, the parameter to the algorithm is only the single word and the modified Naïve Bayesian algorithm, this algorithm works same like original algorithm, but in this case, it is the combination of words. It means first combination of three words, then combination of two words and then single words. The accuracy of the original naïve Bayesian algorithm is 85% and the accuracy of the modified algorithm has been increased, and it is 94% (Trivedi Khushboo, 2012).

As Fiktor Imanuel Tanesab, Irwan Sembiring and Hindriyanto Dwi Purnomo discussion Support Vector Machine is used to classify the opinion into positive, neutral and negative classes. 1000 recorded data was used as a sample data. There were four processes that has been conducted namely, Data Comments, Pre-Processing, Tokenizing and Determine Sentiment with Lexicon Based. In order to determine the percentage of the class sentiment, Lexicon Based method was used. The experiment shows that the proposed method is calculating the percentage weight in their research had used Lexicon Based and Confusion Matrix to know the result of weighting percentage of analysis to SVM. It had been found the result as follows: accuracy 84%, precision 91%, recall 80%, TP rate 91.1 and TN rate 44.8%. (Tanesab, 2017)

Pre-processing plays a very important role in text mining methods and applications. Preprocessing is a first and foremost steps which will help to cleaning a data and increasing the data sparsity and significantly shrinking the feature space. It also helps to process of cleaning and arranging the text for classification purpose. Their proposed methodology uses mainly five steps. In first steps performed the data clean and removed URL, stop words, Punctuation, Strip white space, Numbers from the data. Work performed the number remove process with the help of remove numbers function which is in r studio tool under the TM package. After preprocessing the dataset, we need to determine the Term Document Matrix which describes the frequency of terms that occur in the processed dataset. In R tool, dtm () function used to do all preprocessing in text mining under TM package (Vishal . Shirsat, 2017).

Previous attempts in solving this problem, focused on the use of machine learning methods (N-gram, etc.), ignoring the importance of language analysis which is being used to communicate sentiments. Therefore, they need to find new methods to improve the sentiment classification exploring the linguistic techniques. Arun Meena and Prabhakar work differs from earlier work in four main aspects:

- Their focus is not on classifying each review as a whole but on classifying each sentence in a review.

- They give more consideration/importance to the language properties of the sentence and in understanding the sentence constructs, for each sentence they recognize the subjects of the feeling and the feature being described.
- They concentrate on the effects of conjunctions and sentence constructions which have not been researched for sentiment analysis.
- Their method does not need a training set since it depends on linguistic analysis.

Alaa-Dine Ali Hamouda Fatma-zahraa-taher focused on Arabic Facebook news pages for the task of sentiment analysis. They developed a corpus for sentiment analysis and opinion mining purposes. Then, they used different machine learning algorithms – decision tree, support vector machines, and Naive Bayes - to develop sentiment analyzer. They said the performance of the system using each technique was evaluated and compared with others. Existing supervised learning methods can be readily applied to sentiment classification, e.g., naïve Bayesian, and support vector machines (SVM), etc. took this approach to classify news comment reviews into three classes, positive, neutral and negative. It was shown that using unigrams (a bag of individual words) as features in classification performed well with either naïve Bayesian or SVM.

2.4. Basic Components of Opinion Mining

Basic components of opinion mining are: *opinion holder*, *opinion* and *object*. An opinion holder is either a person or organization that holds a specific opinion on a particular object where as an opinion is a view, attitude, or appraisal on an object from an opinion holder and an object is an entity which can be a product, a person, an event, an organization, a topic, or even an opinion that is criticized or appraised by opinion holder. Basically, there are two ways to express opinions: direct opinions and comparison (Tulu, 2013).

Direct opinions usually describe one object and contain some adjectives that refer to it. For example, **the image quality of your TV program is good**. This sentence consists of an object "TV program" and an adjective "good" which modifies the image quality of a program. The comparative statements mention more than one item and describe some sort of relation. Example: **the image quality of your TV program is much better than ESAT's TV program**. On the other hand, the superlative statements mention more than two items and describe relation of an item with the remaining items. For example, **the image quality of ESAT's TV is best when compared to Oromia's TV.**

2.5. General Sentiment Mining Tasks

In general, the tasks of sentiment mining are: determining document subjectivity, determining document polarity and determining strength of document orientation (Xiaoying Xu, 2009).

Determining document subjectivity: deciding whether a given text has a factual nature or expresses an opinion on its subject matter. This amounts to performing binary text categorization under categories of objective and subjective.

Determining document polarity: decides if a given subjective text expresses positive, negative or neutral opinion on its subject matter.

Determining strength of document orientation: decides whether the positive opinion expressed by a text on its subject matter is weakly positive, mildly positive or strongly positive. Similarly decides whether the negative opinion expressed by a text on its subject matter is weakly negative, mildly negative or strongly negative.

2.6. Types of Opinion Words

There are two main types of opinion: regular opinions and comparative opinions. Regular opinions are often referred to simply as opinions in the research literature review. A comparative opinion expresses a relationship of similarities or differences between two or more than two entities, and/or some of the shared aspects of the entities. A comparative opinion is usually expressed using the superlative or comparative form of an adjective or adverb, although not always. On other hand, regular opinion is a positive or negative sentiment, attitude, emotion or appraisal about an entity or an aspect of the entity from an opinion holder. Positive, neutral and negative are called opinion orientations (also called sentiment orientations, semantic orientations, or polarities).

Bing liu said that We can also classify opinions based on how they are expressed in text, explicit opinion and implicit (or implied) opinion. Explicit opinion is a subjective statement that gives both a regular or comparative opinion. Implicit opinion is also an objective statement that implies both a regular or comparative opinion. Such an objective statement regularly expresses a desirable or undesirable fact. Explicit opinions are easier to detect and to classify than implicit opinions. Much of the current research has focused on explicit opinions. Relatively less work has been done on implicit opinions (Liu, Sentiment Analysis and Opinion Mining, 2012). There are three types of opinion words, these are personal emotion (e.g. happy, delighted, proud, sad, angry, horrified, etc.), appreciation (flexible, stable, efficient, reduced, ideal, backward, poor, highest etc.) and judgment (e.g. active, decisive, caring, dedicated, intelligent, negligent, evil, etc.).

2.7. Levels of Opinion Mining

2.7.1. Document Level Opinion Mining

In this level, the document is taken into consideration as a whole. So, it is classified based on a comprehensive sentiment of the whole document. A major issue in focusing only at the document level is at this level not all the sentences in the document that express opinions are subjective sentences. In order to obtain results that are more accurate after SA, it is more precise to look at each sentence individually.

Classifying a document (e.g. a review, blogs) is based on the whole sentiment expressed by opinion holder. It considers that each document focuses on a single object or entity and contains opinions from a single opinion holder. The main activity in document level sentiment classification is to determine the overall sentiment orientation of the document depends on classes which can be positive, neutral and negative.

2.7.2. Sentence Level Opinion Mining

The sentence level classification considers each sentence as a separate unit and assumes that sentence should contain only one opinion for a single sentence. Sentence-level sentiment analysis has done two tasks subjectivity classification and sentiment classification. An objective sentence presents some factual information, while a subjective sentence expresses personal feelings, views, emotions, or beliefs.

2.7.3. Feature Level Opinion Mining

The aim of feature level classification is to yield a feature-based opinion summary of multiple reviews. It has three tasks. The first one is to identify and extract object features that have been commented on by an opinion holder (e.g. “picture”, “battery life”). The second is to determine the polarity of opinions on features classes: positive, negative and neutral and third task is related to the group feature synonyms (Jagtap, 2013) (Pooja . Ghelani1, 2017).

Sentiment classification at document level and sentence level are not enough to tell what people like and/or dislike, because a positive opinion on an object does not mean that the opinion holder likes everything likewise a negative opinion on an object does not mean that the opinion holder dislikes everything.

2.8. Opinion Classification Technique

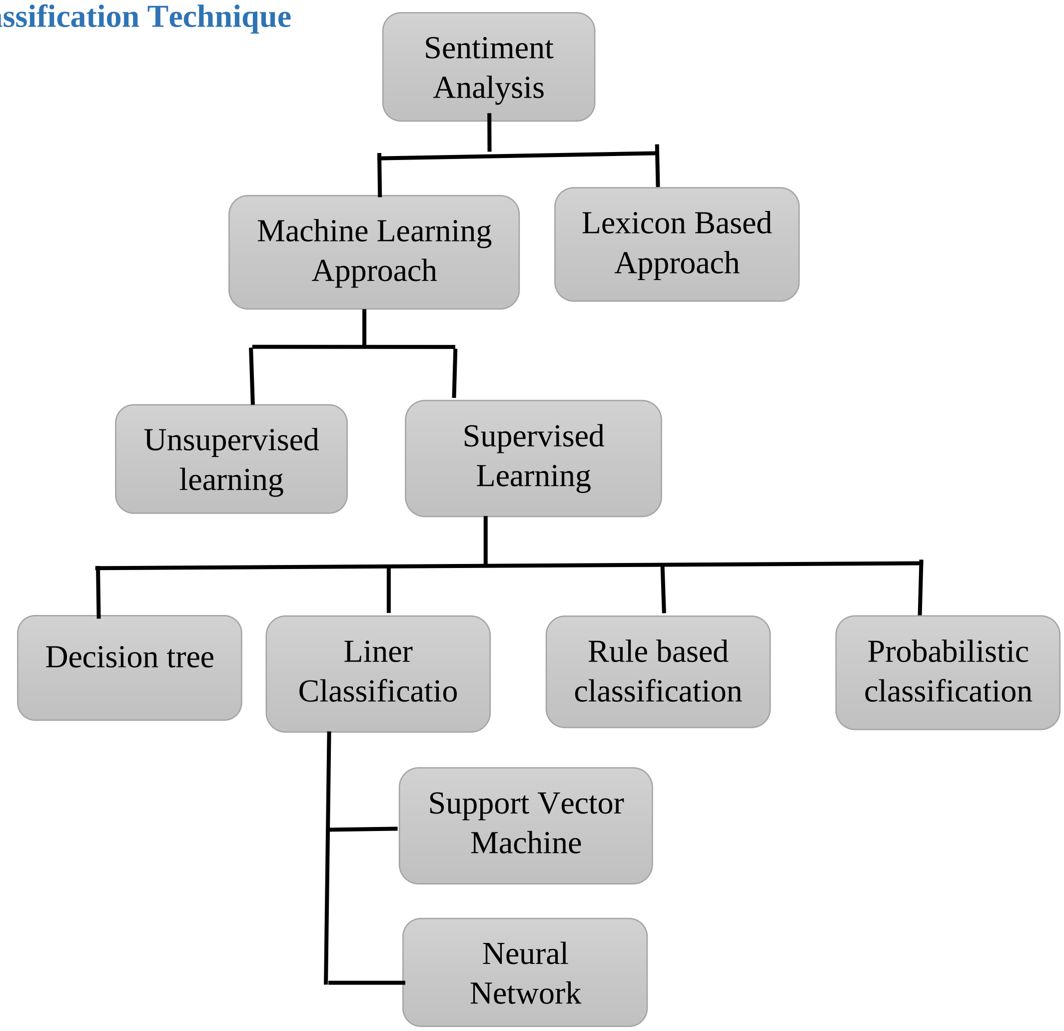

Figure 2: 1 Sentiment classification technique (Poobana, 2015)

2.8.1. Machine Learning Techniques

Machine learning luxuries sentiment classification simply as a special case of topic-based categorization (with the two topics being positive sentiment and negative sentiment). The traditional topic-based categorization attempts to sort documents according to their subject matter (e.g. sports vs. politics). The three standard machine learning algorithms commonly used for sentiment classification are Naïve Bayes (NB) classification, maximum entropy (ME) classification and support vector machine (SVM) classification (Pang and Lillian, 2002).

In this paper we proposed to use liner classification SVM. According to the work of (Pang and Lillian, 2002) the experimental results produced via machine learning techniques are quite good. In terms of relative performance, NB tends to work the worst and SVM tends to work the best although the differences are not very large. While machine learning techniques have been found to produce good results, there are associated disadvantages. Machine learning classification is dependent on the training data so that there is little indication of how the classification would perform in more general cases. The gathering of such a training set is hard, as it involves the gathering and human classification of huge number of different documents. In addition, with machine learning algorithm, it could be difficult to incorporate contextual valence shifters.

Vibha Soni, Meenakshi Patel describe that the main objective of Opinion mining is Sentiment Classification i.e. to classify the opinion into positive, neutral or negative classes. There are basically two approaches first machine learning Or Supervised learning techniques and other unsupervised learning techniques. In their paper an unsupervised lexicon technique is used for Sentiment Classification. A number of unsupervised learning approaches take the credit of first creating a sentiment lexicon in an unsupervised manner, and then determining the degree of positivity (or subjectivity) of a text unit via some function based on the positive and negative (or simply subjective) indicators, as determined by the lexicon, within it.

2.8.2. Lexicon-Based Techniques

This technique uses sentiment and subjective lexicon of terms. The basic idea behind this system is to classify reviews based on how many positive and negative terms are present in the document. This is based on a rule-based classifier where if there are more positive than negative terms then it is considered to be positive. If there are more negative than positive terms, then it is considered to be negative. If there is equal number of positive and negative terms, then it is neutral. When using this technique, it is relatively easy to incorporate contextual valence shifters (Inkpen). The performance of this technique depends on the effectiveness of the lexicon of opinion terms. The main resource used for identifying positive and negative terms in English is the General Inquirer (GI) (Selama , 2010).

GI is a system which lists terms as well as different senses for the terms. For each sense it provides a short definition as well as other information about the term. This includes tags that label the term as being positive, negative, a negation term, an overstatement, or an understatement. Some researchers as in (Inkpen) add extra terms from other resources such as the Choose the Right Word (CTRW) (Selama , 2010). CTRW is a dictionary of synonyms. Adding extra opinion terms from different sources strengthens the efficiency of the lexicon.

2.9. Evaluation of Sentiment Classification

The performance of sentiment classification is evaluated by using four indexes. They are Accuracy, Precision, Recall and F1-score. The common way for computing these indexes is based on the confusion matrix as shown below: (Fatima, 2013)

#	Predicted positives	Predicted negatives
Actual positive instances	Number of True Positive instances (TP)	Number of False Negative instances (FN)
Actual negative instances	Number of False Positive instances (FP)	Number of True Negative instances (TN)

Table 2: 2 Confusion Matrix

These indexes can be defined by the following equations:

Accuracy: is the degree of conformity of a measured or calculated value to its actual (true) value.

$$Accuracy = \frac{TN + TP}{TN + TP + FP + FN} \qquad (2.1)$$

Precision: is the proportion of true positives against the whole positives. Mathematically, it is expressed as:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2.2}$$

Recall or sensitivity: is the proportion of true positives against the whole true or correct data. It quantifies how well the model avoids false negatives [47]. It is also known as true positive rate or hit rate.

$$\text{Recall} = \frac{TP}{TP + FN} \tag{2.3}$$

F1-score: is the weighted average the precision and recall. The relative contribution of precision and recall to the F1-score are equal.

$$F1 = \frac{2 * precision * recall}{precision + recall} \tag{2.4}$$

2.10. Related Works

Joseph. Garciaa, Dylan Valerioa and Prospero. Naval, were discussing Sentiment Analysis Model, the typical Sentiment Analysis Model includes, the data preparation step performs necessary data preprocessing and cleaning on the dataset for the subsequent analysis. Some frequently used preprocessing steps include removing non-textual contents and markup tags (for HTML pages), and removing information about the reviews that are not required for sentiment analysis, such as review dates and reviewers' names (Bongirwar, 2015). The review analysis step evaluates the linguistic features of reviews so that interesting information, including opinions and/or product features, can be recognized. Two commonly adopted tasks for review analysis are POS tagging (Joseph . Garciaa) and negation tagging. After this phase, sentiment classification is performed to get the results.

As Jen-Yuan Yeh, Shihn-Yuarn Chen studies, social tags have been considered to indirectly reflect authorized opinions of taggers. They proposed an unsupervised method which derives implicit sentiment information from social tags to decide, in one document, which sentences are opinionated, as well as to annotate them with proper polarity labels. First, for a social tag, its opinion degree is measured by aggregating the opinion degree of related sentiment words, in proportion to the co-occurrence relations between sentiment words and the tag. Second, the opinion degree of a sentence is determined by a combination function of the opinion degree of the tags, in proportion to the similarity between the sentence and each tag (Jen-Yuan Yeh, 2016). Finally, sentences are arranged in order of their opinion degree, followed by a partition of the ranked list to distinguish sentences into positively opinionated, negatively opinionated, neutral, and non-opinionated ones (Jen-Yuan Yeh, 2016). Their proposed method is examined using the Chinese dataset of the NTCIR Opinion Analysis Task Test Collection and found to perform well. Their Experimental results testify that social tags are positively conducive to opinion analysis. (Jen-Yuan Yeh, 2016)

Jen-Yuan Yeh, Shihn-Yuarn Chen's proposed method can be decomposed into three subtasks. The first subtask identifies sentiment words and assigns a graded sentiment value to each sentiment word. For a social tag, its opinion degree is measured by aggregating the opinion degree of related opinionated words, in proportion to the relations between sentiment words and the tag (Walaa Medhat, 2014). In the second subtask, the opinion degree of a sentence is determined by a combination function of the opinion degree of the tags, in proportion to the similarity between the sentence and each tag. Finally, in the third subtask, sentences are sorted in order of their opinion degree, followed by a partition of the ranked list to distinguish sentences into positively opinionated, negatively opinionated, neutral, and non-opinionated ones.

The main contributions of this work are twofold. First, it offers a method of deriving implicit sentiment information from social tags, which past researches had made little attempt to do so. Second, based on implicit sentiment information of social tags, an unsupervised sentence- level opinion analysis method is proposed to extract opinion sentences and to determine their polarity labels. The proposed method could be practically beneficial to many information processing and management applications. For example, sentiment lexicons can be automatically constructed or increased with the help of sentiment analysis of social tags. By sentence-level opinion extraction and polarity labeling, the effectiveness of opinion-oriented applications, including opinion retrieval, opinion question answering and opinion summarization, can be enhanced (Jen-Yuan Yeh, 2016). (Dhanalakshmi, 2016)

Generally, supervised classification provides more accurate results, although the performance is highly dependent on the applied domain. Unsupervised extraction, in contrast, requires no prior training. The selection of opinion mining techniques tends to be a trade-off between accuracy and generality (Zhou, Movie Review Mining: a Comparison between Supervised and Unsupervised Classification Approaches, 2005).

As Amira Shoukry's and Ahmed Rafea's study there are mainly two approaches for sentiment classification: machine learning (ML) and semantic orientation (SO). The ML approach is typically a supervised approach in which a set of data labeled with its class such as "positive" or "negative" are represented by feature vectors. Then, these vectors are used by the classifier as a training data inferring that a combination of specific features yields a specific class employing one of the supervised categorization algorithms. Examples of categorization algorithms are Support Vector Machine (SVM), Naïve Bayesian Classifier, Maximum Entropy, etc.… (Amira Shoukry, 2012). (Chaudhary Jashubhai Rameshbhai, 2019)

The SO approach is domain-independent, since one lexicon is built for all domains. The approach we have chosen for sentiment classification is the ML approach because we do not have a lexicon for Arabic sentiment word. This approach is based on selecting a set of features to build feature vectors and train a classifier (Amira Shoukry, 2012).

Amira Shoukry's and Ahmed Rafea's approach uses different machine learning classifiers and feature sets. The machine learning classifiers used are Naive Bayes (NB), and Support Vector Machines (SVM). The features used are unigrams and bigrams. The features are done in two distinct components, allowing us to easily try different combinations of classifiers and features until we reach the ones yielding the highest accuracy. (Amira Shoukry, 2012)

Mohammad Ehsan Basiri and Arman Kabiri were discussed Document-level SA aims at specifying an overall opinion expressed in a long text, while sentence-level SA tries to extract opinion from a single sentence. In addition to these two levels some SA researchers target the phrase- or word-level applications in which the orientation or strength of phrases or words is specified to calculate the overall sentiment. Their study concentrates on sentence-level SA. (Mohammad Ehsan Basiri, 2017)

CHAPTER THREE

RESEARCH DESIGN AND METHODOLOGY

3.1. Introduction

In this chapter data preprocessing the design and architecture of the proposed opinion mining model for opinionated Amharic text is described in detail. The proposed model has the following components: pre-processing, opinion analysis, opinion text extraction and opinion polarity labeling classification. Each component is composed of sub components which are the building blocks of the system. Pre-processing is responsible for normalization, tokenization, stemming and stop word removal of comments.

In the sentiment words detection component, all possible sentiment words and contextual valence shifter terms are checked for existence in the corpus. The weight management component encompasses sub systems: weight assignment and polarity propagation. After the weight management is finished, the next step is the polarity classification of the comment. In addition, tools and techniques used for implementing the prototype and the proposed algorithms are also presented.

3.2. Design

Identifying and extracting features, determining opinions regarding identified features, organizing and summarizing unstructured subjective text are the most common activities in text opinion mining. Some characteristics of the Amharic language are taken into consideration for the intended Amharic text opinion mining. Among these characteristics, the first one is devising a means of identifying and extracting nouns as features by analyzing the basic nature of Amharic nouns and the second one is, designing the way of determining adjectives that modify the nouns as opinions by investigating major nature of Amharic adjective words. Moreover, the way of summarizing user comment depending on the features and opinions along these features will be elaborated in this Chapter. Apart from the language characteristics there was a simple user-friendly interface or blog by which a user feeds his/her costumer comment to a database and an interface through which results will be displayed in a graphical form so that the users easily get information they need.

3.3. Architecture of Opinion Mining from Amharic Text Comments

The general architecture of our text opinion mining from Amharic user comment is given in Figure 3:1 The architecture has five major components, these are:

- Dataset
- Data preprocessing (stop word removal, tokenization, normalization, stemming and lemmatization)
- Feature extraction
- Feature selection, and finally
- Opinion Polarity labeling (positive, neutral and negative)

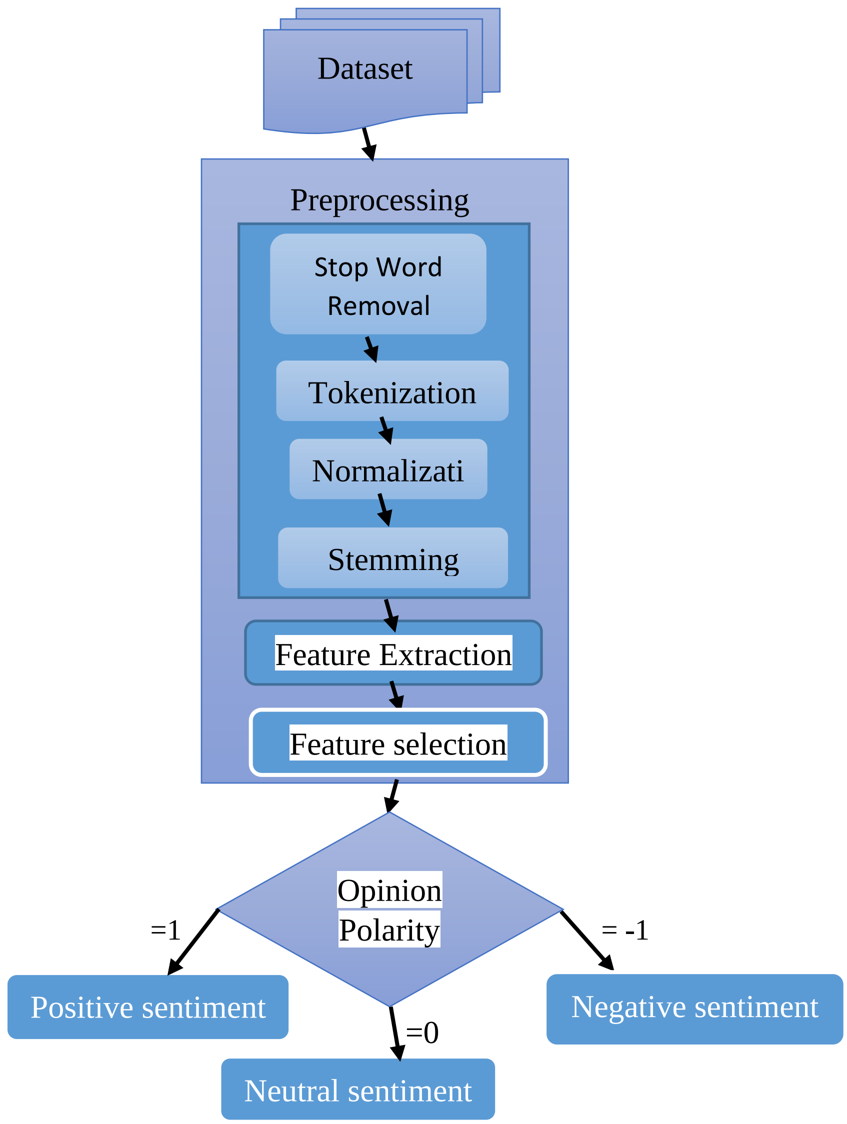

Figure 3: 1 Architecture of Opinion Mining from Amharic text comments

3.4. Dataset Collection

Data collected online from Amhara broadcasting agency Facebook page and YouTube channel of customer comments. For this study two types of dataset will be prepared for training data and testing data to conduct the prototype of opinion mining for Amhara broadcasting agency in Amharic text. For the training dataset, a document which contains a set of representative text from Amhara Mass Media agency sport and business news comment are taken to train our opinion mining algorithm. The data that are collected from the data source are classified in to positive, negative and neutral. For the purpose of this study, we will collect totally 787 datasets. From the dataset 70% for training data and 30% for teste data will be taken.

3.5. Data Preprocessing

This is an important step in any data mining process. This basically involves transforming raw collected comment into an understandable format for NLP models. The difficulty with interpreting the human language is that it is not a set of rules or binary data that can be fed into the system and understanding the context of a reading or conversation between the lines is altogether a different ball game. And Real-world data is often incomplete, inconsistent, and lacking in certain behaviors or trends, and is likely to contain many errors. Data pre-processing is a proven method of solving such issues.

Comments contain information which are not clearly expressive or say meaning and need to be removed. Remove all unwanted punctuations which are not necessary, will help in getting better results through the classification algorithms. Preprocessing tasks are data preparation procedures that should be done before dealing with different text mining techniques. Pre-processing is involved in preparing the input text into a format that is suitable for the opinion mining. The pre-processing stage consists of steps such as tokenization, normalization and stop-word removal.

Tokenize segment text into words, numbers, and symbols. Space used as word separator. A sentence splitter identifies the boundaries of sentences. A passage indexer constructs a vector representation for every sentence in a document. Further, tag normalization is performed to group synonymous tags together and Data cleaning which involves removal of objective text (non-opinion text) from the given reviews. Opinion holder’s reviews may not be genuine reviews rather facts or questions which cause confusion for the sentiment analysis/opinion mining procedure and resulting in unreliable output. Furthermore, we will try to correct spelling errors by realizing the intention of opinion holders. For instance,

መባየል corrected to ሞባይል ፣እሰከሪን corrected to እስክሪን ፣ብረደበንድ correct to ብሮድባንድ ፥ብዝንሰ corrected to ቢዝነስ etc.

We collect opinions from different individuals, all online comments from different opinion holders will be posted on the blog, so we have to organize the collected data. Multiple comments from different sources will be stored into a coherent text database that we will be designed for this purpose. Normalizing different letters of Amharic script that have the same sound, homophone characters, while integrating the reviews, for instance we will change ኸ and ሐ to ሀ. (Selama , 2010). In this section, the proposed method that combines the Amharic word extraction technique and the sentiment analysis technique is described.

The proposed method consists of the following steps: we will collect comment from internet (i.e Amhara broadcasting agency Facebook page, YouTube posts and if there is comment space from their website), collected comment will be preprocessed and opinions are analyzing then the analyzed text can be extracting and then the extracted opinionated text are labeling in to its polarity. The stop words and stemming words are removed at the stage of preprocessing. The extracted text comments are analyzed by reviewer and classify the text into positive, neutral and negative then the product is ranked.

Feature Extraction and Feature selection is most important task of opinion mining. There is more than one name for the same aspects. For example, someone use “የኳስ ጨዋታው ጥሩ ነው” or someone use “የኳስ አጨዋወት ገራሚ ነዉ” but meaning of ጨዋታዉ and አጨዋወት is same. Hence also recognize same synonym of the different aspects and design an aspect matrix.

3.5.1. Stop Word Removal

Stop words are words that occur more and more time in the document, but are not relevant or have no impact to classify opinions. This pronoun, prepositions, conjunctions have no specific meaning,“i"(እኔ),"a","an",”is”(ነው),"are"(ናቸው),"as"(እንደ),"at"(በ),"from"(ከ), "in"

(ለ፣ወደ፣በ), ”this” (ይህ),"on"(በ...ላይ),"or"(ወይም),"to"(ወደ),"was"(ነበር),"what"(ምን), etc. are example of stop word, so these types of words has been removed.

Stop words are low information bearing words such as “ነው” or “ና”, typically appearing with high frequency in the document. Stop words may be context dependent. High frequency words have higher variance and effective weight in many methods, causing them to be erroneously selected as features due to sample noise. There is no definite list of stop words found, which all tools use, and such a filter is not always used. Some tools specifically avoid removing them to aid phrase search. Like other languages, Amharic has non-content bearing words, which are called stop words.

Usually words such as articles (e.g. ‘ያኛው’, ‘ይሄ’), conjunctions (‘ና’, ‘ነገርግን’, ‘ወይም’) and prepositions (e.g. ‘ውስጥ’, ‘ላይ’) do not have a significant discriminating power in the meaning of ambiguous words, we filtered the sense examples with a stop-word list, to ensure only content words are included. In addition to stop words, names of people and places also filtered from the sense examples, as they are not related to the meaning of words. In our approach, “stop words” like ‘ነው’, ‘እስከ’, ‘እንደ’, etc. are discarded from input texts as these words are meaningless to derive the “sense” of the particular sentence.

Teshome Kassie describes about stop words that since stop and function words have no discriminating power for information retrieval, they must be removed and they list the stop words. (Teshome, 2009)

Then, the text containing meaningful words (excluding the stop words) pass through morphological analysis.

```
Read stop word list file
Open the file for processing
Do
        Read the content of the file line by line
        Assign the content to string
        For word in string split by space
                If word in stop word list
                        Remove word from the index term
                Else
                    Continue
                End if
        End for
While end file
```

Algorithm 3: 1 Stop word removal

3.5.2. Tokenization

The first step in the preprocessing of the input text is tokenization, which is also known as lexical analysis. The tokenization takes the input text provided from a user and tokenizes it into a sequence of tokens, which is the process of breaking a stream of text into words, phrases, symbols, or other meaningful elements called token and finally it gives the tokens to the next phases. Token is the smallest unit that will be extracted from the input text before performing word sense disambiguation. In order to find the boundaries of the sentence the input text is segmented in to tokens. For most languages, white spaces and punctuation marks are used as boundary markers. The Amharic language has its own punctuation marks which demarcate words in a stream of characters which includes ‘hulet netb’ (:), ‘arat netb ‘(።), ‘derib sereze’ (፤), ‘netela serez’ (፣), ‘exclamation mark’ (!) and ‘question mark’ (’?’).These punctuation marks do not have any relevance to identify the meaning of ambiguous words using WSD. Therefore except ‘arat neTb‘and ‘question mark’ which are used to detect the end of the sentence, all other punctuations are detached from words in tokenization process.

The tokenization algorithm is shown in Algorithm 3.1 below.

1. Open the corpus
2. While not end of file is reached do
        For each character in the corpus
            If the character is Amharic word delimiters then
                Remove the character
            End if
        End for
3. End while
4. Close files

Algorithm 3: 2 Tokenization Algorithm

3.5.3. Normalization

Normalization is performed on the word tokens that result from text segmentation. In the Amharic Language, two types of normalization issues arise. One is the identification and replacement of shorter forms of a word that is written using forward slash "/" or period "." And or acronyms. An example is the replacement of "መ/ር" by "መምህር". The second normalization issue is the identification and replacement of Amharic alphabets that have the same use and pronunciation, but they have different representations of alphabets. The replacement is made using a representative Amharic alphabet from a set of similar Amharic alphabets. For example, the word "sun" can have more than six representations in Amharic: ጸሀይ, ጸሐይ, ጸኀይ, ፀሀይ, ፀሐይ, ፀኀይ, these words differ by their characters: "ፀ" and "ጸ" ፣ "ሀ፣ሐ and ኀ" have similar usages and different forms, They need to be converted to a single representative character such as "ፀ" and" ሀ".

1. Set a buffer to empty

2. Read a character

I. If the character is one of ሀ,ሐ,ሰ,ሠ,ኀ,አ,ዐ,ጸ,ፀ, or their orders call a component that can handle their replacement.

i. add the character to the buffer

ii. go to step 2

II. Else if the character is "/" or"."

i. call a component that can handle such characters

ii. return the string as a word

iii. Go to step 1

III. Else if the character is a white space or one of the punctuation marks

i. Return what is in the buffer as a word

ii. Go to step1

IV. Else

i. Add the character to the buffer

ii. Go to step 2

Algorithm 3: 3 Identification and Replacement of Shorter Forms of a Word

1. Open the corpus

2. While not end of corpus file do

For each character in the corpus

If the character is ሐ፣ ኀ፣ ኸ or any order then

Changed to ሀ

Else if it is ሠ *or any order of it then*

Changed to ሰ

Else if it is ጸ *or any other order of it then*

Changed it to ፀ

End if

End for

3. End while

Algorithm 3: 4 Identification and Replacement of Amharic Alphabets

3.5.4. *Stemming*

It converts word into its grammatical root form. Most of the time words that appear in a document have many morphological variations. The process of stemming is an attempt to reduce a word to its stem or root form. Most often such common variants happened due to suffixing and prefixing. Stemming will bring the different forms of the word into common forms. Stemming technique converts word like "teach" (አስተማረ)," teacher (አስተማሪ)," teaching" (ማስተማር)," teaches" አስተማረ," teachers" (አስተማሪዎች) to root word teach(አስተማረ).

The stemmer developed for this study is based on worku kelemework (Kelemework, 2013). In such case, rules are applied to find the stem of Amharic words. The rules to remove prefix or suffix from a given word may not hold true always. For instance, removing 'ት'('ti') from the word 'ሴት' ('woman') would give 'ሴ'('sie'), which is meaningless; and removing 'ከ' ('ke') from 'ከተማ' ('town') gives 'ተማ' ('tema'), which does not represent the original meaning. Hence, two exception lists are prepared for which affix removal rules do not applied; List of words that prefix removal rule does not hold true and list of words from which suffix removal rule is not applied.

List of words that prefix removal rule does not hold true and list of words from which suffix removal rule is not applied. The stemmer developed takes words as an input and removes prefix of the word. After the prefix is removed, the word is again checked if it lasts with suffix in the suffix list, if so, the suffix is removed from the word.

```
Read prefix list file
Open the file for processing
Do
    Read the content of the file line by line
    Assign the content to string
    For word in string split by space
        If length of word is greater than two
            If word starts with prefix
                Remove prefix from the word
            Else
                Continue
        Else
            Continue
    End for
While end file
```

Algorithm 3: 5 Prefix striping

```
Read suffix list file
Open the file for processing
Do
    Read the content of the file line by line
    Assign the content to string
    For word in string split by space
        If length of word is greater than two
            If word ends with suffix
                Remove suffix from the word
            Else
                Continue
            Else
                Continue
    End for
While end file
```

Algorithm 3: 6 Suffix striping

3.6. Feature Extraction

Feature extraction is transforming the existing features into a lower dimensional space. In machine learning how to represent the data is a critical question. Both the training and the test data must be represented in some way in order for a machine learning algorithm to learn and build a model. The ways data can be represented are feature-based or bag-of words representation. By feature we mean that to capture the pattern of the data selected and the entire dataset must be represented in terms of them before it is fed to a machine learning algorithm. Feature extraction is the process of transforming what is essentially a list of words into a feature set that is usable by a classifier. The TF-IDF and *bag-of-words* models are the simplest method; it constructs a word presence feature set from all words of an instance.

The experiment performed on different feature subsets which comprise the most informative features of the corpus: the entropy of the distribution of each word over the different output classes are calculated, and the words with the lowest entropy (or highest information gain) are considered the most relevant features for the classifiers. To measure entropy, the frequency distribution of a feature (in this case a word) over the output classes is computed. These feature selection methods compute a score for each individual feature and then select top ranked features as per that score.

Term frequency (tf)

The count or number of times each term (t) occurs in each document (d) is called its term frequency. From the lists of words that we get from magazines, newspapers, and blogs as inputs, we can calculate the frequency of each word in the documents and it shows some measure of term density in a document. This measure is very important to determine the most valuable document to the query terms from a set of documents. The best way to apply is by eliminating the documents that do not contain all the terms we need. To further differentiate, we have to count the number of times each word is coming in a document and then sum up them together. This sum is what we call "term frequency". Thus, terms with high frequency are considered to as less informative terms in the whole document. And most researchers used this measurement for the stop words list identification for different world languages. Term frequency a term can be defined as

$$tf = (\frac{tf, d}{\sum ft, d}) \quad (3.1)$$

Where,

tf, d is Term frequency in a document and $\sum ft, d$ total word number of terms of documents

Inverse Document Frequency (idf)

Inverse Document Frequency is the measure of the uniqueness of a term from the document. It shows whether a term is common or infrequent in the given document. In the computation of term frequency, we have considered all the terms are significant. In the Amharic text, although we all know that few terms like "እና", "ነው", and "ግን" appear a lot of times in the document but they are having little importance. Hence, we must minimize the weight of frequent occurring terms and increase their rareness. The inverse document frequency for any given term is defined as,

$$idf = \log(\frac{N\_document}{N\_document\_containing\_term}) \quad (3.2)$$

Term Frequency Invers Document Frequency $(TFIDF)$

term frequency-inverse document frequency (TF-IDF) is a statistical measure that evaluates how important a word is to a document in a collection of documents. This is done by multiplying two metrics: how many times a word appears in a document and the inverse document frequency of the word across a set of documents. It has many uses, most importantly in automated text analysis, and is very useful for scoring words in machine learning algorithms for Natural Language Processing (NLP).

Multiplying the results of TF and IDF results the TF-IDF score of a word in a document. The higher the score, the more relevant that word is in that particular document. To put it in more formal mathematical terms, the TF-IDF score for the word t in the document d from the document set D is calculated as follows:

$$tfidf(t,d,D) = tf(t,d).idf(t,D) \tag{3.3}$$

Where:

$tf(t,d) = \log(1 + freq(t,d))$

$idf(t,D) = \log\left(\frac{N}{count\left(d \in D : t \in d\right)}\right)$

N-grams

The tokenization of a document will produce features with frequent occurrence, but identifying multiple token features can produce rarer, highly specific features, such as ***በጣም ጥሩ*** (very good) or ***እጅግ በጣም ጥሩ*** (Excellent). This is called an n-gram, where n determines the number of consecutive tokens used to produce the features. The simplest approach is to treat the consecutive words as a feature and let feature selections (FS) determine which are useful for prediction. The most popular n-grams are unigrams (n= 1), bigrams (n= 2) and trigrams (n= 3). Most probably removal of stop words helps relevant higher order n-grams reduced to a bigram or tri-gram. Since these co-occurrences will be less likely to be found in the same document or others. *Character* n-grams have proven to be even more useful than *word* n-grams, for example in language classification.

Word2Vec

The first step in a machine learning text classifier is to transform the text into a numerical representation usually a vector. Usually, each component of the vector represents the frequency of a word or expression in a predefined dictionary (e.g. a lexicon of polarized words). This process is known as feature extraction or text vectorization and the classical approach has been bag-of-words.

The transformation from words to vectors is also known as *word embedding*. The reason for this transformation is so that machine learning algorithm can perform linear algebra operations on numbers (in vectors) instead of words. More recently, new feature extraction techniques have been applied based on word embeddings (also known as *word vectors*). This kind of representations makes it possible for words with similar meaning to have a similar representation, which can improve the performance of classifiers.

3.7. Feature Selection

Feature selection is a process where we automatically select those features in our data that donate most to the prediction variable or output in which we are interested. Selecting a subset of the available features without alteration. While performing any machine learning task feature selection is one of the important steps. A feature in case of a dataset just means a column. When we get any dataset, not essentially every column (feature) is going to have an influence on the output variable. If we add these irrelevant features in the model, it will just make the model poorest (Garbage in Garbage Out). That is why we need doing feature selection. Having irrelevant features in your data can decrease the accuracy of many models, especially linear algorithms like linear and logistic regression.
Feature selection can be done in multiple ways but there are broadly three categories of it:

- Filter Method: As the name suggest, in this method, you filter and take only the subset of the relevant features. The model is built after selecting the features. The filtering here is done using correlation matrix and it is most commonly done using Pearson correlation.

- Wrapper Method: A wrapper method needs one machine learning algorithm and uses its performance as evaluation criteria. This means, you feed the features to the selected Machine Learning algorithm and based on the model performance you add/remove the features. This is an iterative and computationally expensive process but it is more accurate than the filter method.

- Embedded Method: Embedded methods are iterative in a sense that takes care of each iteration of the model training process and carefully extract those features which contribute the most to the training for a particular iteration. Regularization methods are the most commonly used embedded methods which penalize a feature given a coefficient threshold.

3.8. Tools and Techniques

3.8.1. Tools

We used different environments and tools in order to accomplish our aims, Python programming language is used to develop the model. It is a popular programming language. It was created in 1991 by Guido van Rossum. Python is an interpreter for extract data from internet and implementing the algorithms, which is object oriented, high level programming language with a dynamic semantics. It is high-level built in data structures, combined with dynamic typing and dynamic binding; make it very attractive for Rapid Application.

The python programming language is a dynamically typed, object oriented, interpreted language and it is great for natural language processing (NLP) because it is simple, easy to debug (exceptions and interpreted language), easy to structure (modules and object oriented) and powerful for string manipulation. We used python 3.8 version because it is possible to use encodings different than ASCII in python source files. As a result, Amharic language characters are directly interpreted by python 3.8 and above versions without the need to go for transliteration or feeding the Unicode representation of the characters. All the source codes and rules of the prototype are written in python 3.8 compatible format because this version support backward compatibility. (Selama , 2010)

Facepager: tool was made for fetching publicly available data from Facebook, Twitter and other JSON-based APIs. In addition, we are using Facebook, Instagram or tweeter online comment extractor https://exportcomments.com/ which extracts a comment to excel file.

Basically, we are using online YouTube comment scraper for extracting you tub comments. This website allows you to download (scrape) all comments from a given YouTube video. The results include the comment text, username, date and other information. The comments can be downloaded as JSON or CSV *(can be opened in Excel).* This project is open source and the source code is available on GitHub. Here is the link http://ytcomments.klostermann.ca/.

3.8.2. Technique

In the field of opinion mining, the problem of identifying and extracting features and opinions and then generating the summary can be tackled using different approaches. Some of the notable ones are rule-based, statistical, and hybrid approaches. From the definitions of the aforementioned approaches and techniques, it is possible to infer that statistical approach has an implication on the design and development of the text opinion mining system for Amharic language. Therefore, the design and development of this thesis work is based on the machine learning approach

CHAPTER FOUR

EXPERIMENTS AND RESULT DISCUSSION

4.1. Introduction

Supervised techniques which is Support Vector Machin were used for conducting the experiments. The procedure is, as is standard in supervised machine learning tasks, first training a classifier on pre-classified training data and then evaluating the performance of the classifier on unlabeled set of test data. We selected to work with the Natural Language Toolkit (NLTK). This package is equipped with several classifiers (i.e. NB, ME, SVM and the python classifier library). All programming has been done in the Python programming language and executed in the programming environment Window 10 python interactive shell.

In this study, Experiments were done by using TF-IDF word extraction and most informative words with the two learning algorithms Naïve Bayes and Support vector machine classifiers. All the results are presented in the subsequent section. All works are done using NLTK classification packages and python programming.

4.2. Testing Environment

The testing has been done on a laptop computer with Windows 10 professional operating system, Intel(R) core (TM)i5-5200U CPU@ 2.20GHz processor, 8 GB RAM and 700 GB hard disk. Python 3.8 was installed and configured for the testing of the proposed model. Every text file has been saved with UTF-8 encoding system for Unicode characters processing.

4.3. Data Collection and Preparation

As presented in the previous chapters, for conducting experiments we have considered the Amhara broad casting sport and business news comment domain. The main reason why we used the Amhara broadcasting sport and business news comment domain is due to that the costumer comments freely on sport and business news rather than politics. As a result, it is relatively easier and more manageable to collect Amharic sport and business comment on Amhara broad casting agency automatically on their Facebook and YouTube channel than any other domains. This is because; it is possible to collect data from Amhara broadcasting agency easily. In addition, sport and business viewers can write comments freely as compared to other domains such as politics, products, etc. Hence, most of the Amharic sport and business news comment we used for conducting the experiments are collected automatically by extracting using extractor tool as discuss in the previous chapter and categorize in to three labeled classes. These are positive, neutral and negative.

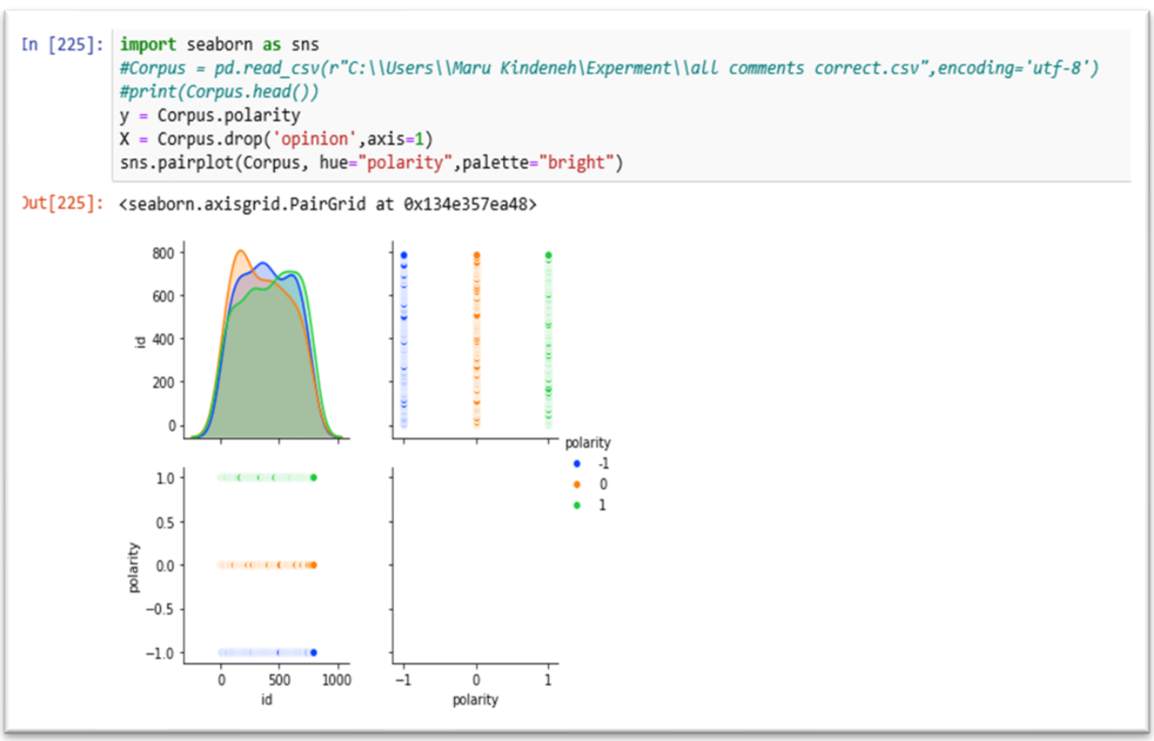

Figure 4: 1 Frequency Distribution Plot

As a result, a total of 787 sport and business news comments are collected from Amhara broad casting Agency Facebook and YouTube Channel. After the data is collected, preprocessing tasks were applied to construct the final data set (data that are used as input for the modeling tool) from the initial raw data. Data preparation tasks are usually performed multiple times depending on the quality and size of the initial data set. A task includes cleaning, normalization, tokenization; stop word removal and stemming of the data were performed to come up with the final suitable dataset for the selected algorithms. The data may be further processed by feature selection and extraction to reduce dimensionality (Abreham , 2014).

```
In [55]: import matplotlib.pyplot as plt
         import seaborn as sns
         rowsums = Corpus.iloc[:,2:].sum(axis=1)
         x=rowsums.value_counts()

         #plot
         plt.figure(figsize=(5,4))
         ax = sns.barplot(x.index, x.values)
         plt.title("Multiple categories per comment")
         plt.ylabel('# of Occurrences', fontsize=12)
         plt.xlabel('# of categories', fontsize=12)

Out[55]: Text(0.5, 0, '# of categories')
```

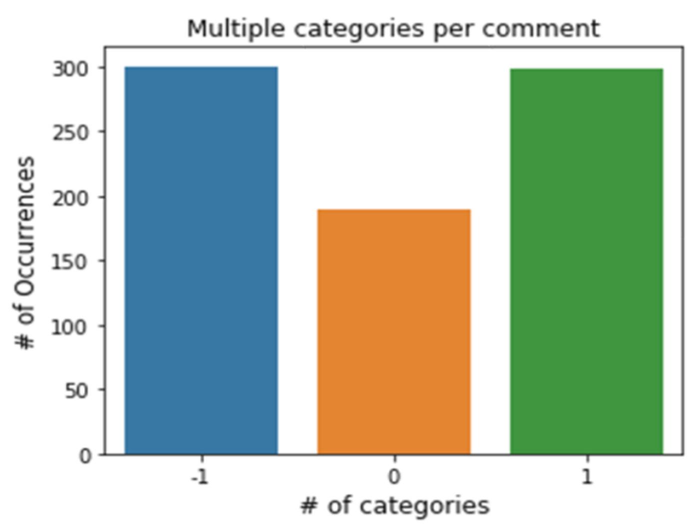

Figure 4: 2 Number of comments in categories

In Figure 4.2 is the snipping shoot of a code that show how many numbers of comments are categorized in each category. There is number of comments per categories, as show in figure.

4.4. Evaluation Procedures

The experiment is done to measure the overall performance of the developed supervised machine learning opinion mining model. Out of the available corpus, the portion of the training set is 550 posts and the remaining 237 posts are set aside as test data set. Each of the posts in the test set is used as an input post one by one and the system returns their polarity. These set of observed polarity values are compared to the annotated label polarity values which is our reference set. The implementation results well be described in the forthcoming section.

4.5. Evaluation Results

The most commonly used evaluation metrics in opinion mining are accuracy, precision, recall and F-score (Wondwossen Philemon).There are three polarity classes in our case (‘positive’, ‘neutral’, ‘negative’). in our work the implementation we are performing were calculate the accuracy for the classifier as a whole.

4.6. Experimental Results and Discussion

Experimental Result Using SVM

Support Vector Machines (SVM) is just one out of many algorithms we can choose from when doing opinion miming. Like naive Bayes, SVM does not need much training data to start providing accurate results. Although it needs more computational resources than Naive Bayes, SVM can achieve more accurate results.

In short, SVM takes care of drawing a “line” or hyperplane that divides a space into two subspaces: one subspace that contains vectors that belong to a group and another subspace that contains vectors that do not belong to that group. Those vectors are representations of your training texts and a group is a tag you have tagged your texts with.

SVM is categorized as supervised learning which considered as heuristic algorithm. The main idea in SVM is to determine a hyper plan that optimally separates classes. there is only one hyper plane that provides maximum margin between the two classes. For nonlinear equations, the data be mapped into a higher dimensional space through some nonlinear mapping functions. Kernel function is used to solve classification function. In this paper, polynomial Function is used as the kernel function in order to get better accuracy because we use three classes. There are four basic kernels functions: (Pramudyana Agus Harlianto, 2017)

$$- Linear: K\left(xi,\, xj\right) = xi^{T} xj$$
$$- Polynomial: K\left(xi,\, xj\right) = \left(yxi^{T} xj + r\right)^{d}, y > 0$$
$$- RBF: K\left(xi,\, xj\right) = exp\left(-y|\ xi - xj|2\right), y > 0$$
$$- Sigmoid: K\left(xi,\, xj\right) = tanh\left(yxi^{T} xj + r\right)$$

In this section we measure the overall performance of our model accuracy which scores 83.24% in SVM algorithm and 78.32% in Naive Bayes algorithm. The training and validation datasets are evenly distributed over the underlying 3(positive, neutral and negative) classes. To improve the accuracy, we need to clean the data more and increase the data size specially training data size.

Algorithm	Accuracy
SVM	83.24%
Naive Bayes	78.32%

Table 4: 1 Accuracy in SVM and Naive Bayes Algorithm

4.7. Discussion

Table 4.1 show the experimental results for the effectiveness of proposed model in extracting features and determining polarity of opinion words along identified features for Amhara mass media Agency Facebook and YouTube user comments domains. The result under experiment, Table 4.1 shows the performance of the method in support vector machine and Naive Bayes algorithm. From the experiment we could observe performance of 83.24% in SVM and 78.32% in Naive Bayes. We try to clear our data as possible but it needs to be more preprocessing surely the performance will be increased if the data cleans more and our data is 787 that is small data so it is also better maximize the data to score better performance but we were limited to add more data because the difficulty of extracting data on internet. Accuracy is the degree of conformity of a measured or calculated value to its actual (true) value. The accuracy of an experiment value is a measure of how closely the experimental results agree with a true or accepted value.

The experiment result uses *tfidf* feature extraction method which indicates the most frequent words. We observe in the experiment the result varies if we feed different seeds, when we set a random seed, we observe constant results whenever we run our code. and also, the accuracy will increase when we seed more random sets.

Our training tata from 787 collected comments are 70% the test set is 30% which is small data, that is why we score 83.24% accuracy. To collect the comment there is a difficulty environment due to the lack of clear comments and also, we have to use data extractor tools so that we need a good internet connection. Additional obstacle is the extracted data contains so many bad characters such as symbols, html tags.

We take more times for extracting the comment form the domain source and for preprocess the extracted comment to make suitable for the algorithm. We try to show the preprocessing steps in the previous chapter in different algorithms. because we are using supervised algorithm which needs training for learning than the algorithm testes depending on the training so to train the algorithms, we will label the tata. surly the accuracy will be increased with the increasing training data because the algorithm learns more and more from the data.

4.8. Challenge to validity

There are many challenges in opinion mining. The first is that people do not always phrase opinions in a same way. A second challenge is an opinion word that is considered to be positive in one state may be considered negative in another state. Most traditional text processing depends on the fact that small differences between two pieces of text don't change the meaning very much. In opinion mining, however, "ዜናዉ ጥሩ ነው" is very different from "ዜናዉ ጥሩ አይደለም". People can be dissimilar in their statements. Farthest reviews will have positive, neutral and negative comments, which is slightly manageable by analyzing sentences one at a time. However, in the more annular medium like comments or blogs, the more likely people are to join different opinions in the same sentence which is easy for a human to understand, but more difficult for a computer to balances. Sometimes even other people have difficulty recognizing what someone thought based on a short piece of text because it’s shortage context. Amharic language opinion mining challenges due to its complexity of the morphology.

5. Summary

Generally, in natural language processing (NLP), the classification or opinion mining (OM) is regarded as a specific case of test classification. Despite the number of classes in opinion mining being small, the process of opinion classification is complex than the traditional topic text classification (Bilal Saberi, 2017). The classification in topic text classification depends on the use of keywords; however, it does not work efficiently in case of opinion mining. The nature of the problem defines other difficulties in opinion mining. The negative opinion may sometimes be represented in a sentence without using any notable negative words. In addition, there is a fine line between whether a sentence should be considered subjective or objective. Identifying the opinion holder, the person who voices sentiments in the text is the most complex task in opinion mining. The sentiment analysis greatly relies on the subject or field of the data. The words may sometimes have a positive sentiment in a particular field, and the same words may have another polarity sentiment in a different field.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATION

5.1. Conclusion

Research in sentiment analysis for the Amharic language has been very limited considered to other languages like English whether at the sentence-level or document-level. In this study, we investigated the ML approach for sentence- level sentiment analysis for Amharic using 787 comments from Amhara broadcasting agency Facebook page and YouTube channel comments. In our approach, we applied the TF-IDF feature vectors to the SVM Classifiers. Problems with regards to the training data is that some comments may occur many times without any change. This gives a misleading boosting to the weight of the terms in the sentence; sometime comments are more than 2 times in the corpus. Also, the problem of opinion spamming or untruthful opinions could affect the accuracy of the classification as then the classifier will be built on a misleading comment. On the other hand, one thing with regards to the testing comments is that the comment may contain dual opinions, thus its sentiment to some extend is ambiguous.

5.2. Recommendation

For future work, we will continue in this line of research by improving our corpus using some techniques such as enlarging or fine-grained annotation. Moreover, we will focus on adding some stylistics features, in addition to considering adding some semantic features thus creating a hybrid approach that combines both the ML and SO approaches. This will be accomplished by building a more comprehensive list of all the positive, neutral and negative sentiment words for the Amharic dialect since there doesn't exist any of them. Also, negations and valence shifters will be considered as a feature in ML approach because their presence in the sentence can result in changing the sentiment of the whole comment like "ጥሩ - nice" implying positive sentiment if preceded by "ጥሩ አይደለም– not good" would then imply negative sentiment. And finally, neutral sentiment comment has to be considered as in real world applications neutral comments cannot be ignored.

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